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Multi-criteria robust optimization framework for bridge adaptation under climate change

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ABSTRACT

In order to adapt civil infrastructure to changing climate conditions, quantifiable and deep uncertainties must be integrated into the decision-making process. The quantifiable uncertainties, i.e. variability for which a likelihood can be defined, are typically integrated into the management process by considering the reliability or risk level of a structure. The deep uncertainties, i.e. the variability for which a likelihood cannot be defined, are beginning to be integrated in the decision making process as a few robust decision making procedures have been proposed. However, the deep uncertainty associated with the multiple feasible future climate scenarios also provokes a "wait and see" mentality for some decision makers, causing the flexibility of a strategy to be valued. This paper introduces the Gain-Loss Ratio (GLR) as a metric that systematically quantifies what may be gained by postponing adaptation while also considering what is lost with the delay. Additionally, bi-objective optimization models for optimizing bridge adaptation strategies under deep uncertainties are proposed; the advantages and disadvantages of each are highlighted as they pertain to the management of a typical riverine bridge. Two rivers are considered that have comparable climate change trends as those predicted for the Columbia and Mississippi Rivers. It is demonstrated that the desire for flexibility may be justified for certain locations, but may be detrimental in others.

1. Introduction

The uncertainties of climatechange increase the difficulties facing decision makers when it comes to determining optimal adaptation strategies for civil infrastructure[1–3]. The challenges lie in the efficient integration of both quantifiable and deep uncertainties while also accommodating the risk attitudes and skepticism of individuals within the decision making group. The field of adaptation engineering focuses on ensuring that current and new assets are protected from both near- and long-term changes in climate conditions [4,5]. It is an active field of research, with substantial emphasis on managing civil infrastructure [6–8]. This paper proposes a methodology that balances the benefit of adapting bridges with the flexibility of a strategy. Additionally, both the quantifiable and deep uncertainties associated with the climate change are systematically integrated into optimization formulation.

Quantifiable uncertainties are those for which a probability of occurrence is well defined; whereas deep uncertainty refers to instances where probabilities cannot be agreed upon [4,9]. Examples of quantifiable uncertainties may include those associated with the physical properties of a structural system, the natural variability of wind, precipitation, and flooding, and the variability in structural deterioration processes. The presence of these uncertainties typically precipitate the use of vulnerability assessment methodologies to evaluate the effectiveness of adaptation strategy. The probability of failure, reliability, or risk have been integrated in optimization routines in order to determine optimal strategies [10–14].

Deep uncertainties, those for which probabilities cannot be defined, may include future economic and/or climate scenarios [15,4]. In the climate adaptation engineering, deep uncertainties stem from both the Representative Concentration Pathways (RCPs) used to define greenhouse gas trajectories and the Global Climate Models (GCMs) to predict future climate scenarios. Since no likelihood can be assigned to the different RCPs [5] and there is no consensus on which GCM is the most applicable [16], there is no probability that can be objectively assigned to the occurrence of future climate scenarios. This represents a unique challenge to decision makers who must either aggregate the future climate scenarios into one or otherwise account for all potential scenarios in the decision-making process.

The deep uncertainties of climate change pose two unique problems. First, the scenario uncertainty drives a desire for flexibility, as well as efficiency, in an adaptation strategy. Second, decision makers must aggregate the future climate scenarios into one, or otherwise account

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for all potential scenarios in the decision-making process.

Typically, the efficiency of an adaptation strategy is quantified by the benefit, Benefit-Cost ratio (BCR) or Net Present Value (NPV), all of which have been integrated into the development of management strategies [11,19]. The benefit of an adaption strategy represents the reductions in risk achieved by that strategy. BCR and NPV consider both the benefit for society, and the economic efficiency of the action. However, some decision makers may also prefer to consider the option value in a strategy (i.e. the value of the flexibility of the strategy). This is related to the timing of adaptation: postponing adaptation may allow the decision maker to observe climate conditions and wait for improved climate information to become available. This then allows the flexibility of adapting at a more favorable time or not adapting. While the desire for flexibility in adaptation strategies has been identified and discussed qualitatively [4,20,21], there is no systematic methodology for assessing the flexibility of an adaptation strategy as it pertains to the management of structural assets.

When decision makers have identified the metric with which to evaluate an adaptation strategy, they must still determine how they are going to aggregate the performance across all scenarios. Robust optimization models have been developed to find optimal strategies against potential scenarios without requiring the probabilities of occurrence of scenarios to be known. Non-probabilistic robust optimization models, such as maximin or maximax models, consider the performance of the adaptation strategy against all scenarios without assigning a probability of occurrence to them [17]. Maximin formulations typically optimize over the worst-case scenario, while maximax formulations typically optimize over the best possible scenario. By choosing the formulation of the problem, the decision makers are predisposing themselves to a particular preference: maximin and maximax formulations assume a pessimistic and optimistic outlook on future scenarios, respectively. Alternatively, a robustness index can be used to assess the variability of the performance of a strategy across all potential scenarios [9]; thus, aggregating the response across all scenarios and enabling the use of a maximization optimization formulation. When optimizing using the robustness index, the decision makers are not giving preference to any one scenario, but consider how well the strategy performs across all scenarios. It implicitly assigns the same probability of occurrence to all scenarios. Thus, this last model falls into the category of a probabilistic robust optimization model, i.e. a stochastic optimization model.

This paper proposes a Gain-Loss Ratio (GLR) to account for the potential gains and the potential losses associated with the delay. This metric systematically assesses the value in delaying adaptation in order to achieve a flexible strategy. Furthermore, this paper proposes bi-objective robust optimization models that simultaneously optimize the conflicting objectives of efficiency (as defined with the BCR) and the flexibility (as defined with the GLR). The methodology is applied to two illustrative examples; both include a typical bridge over a river vulnerable to climate changes. The climate change trends in the two examples are modeled after expected trends in the Mississippi and Columbia Rivers in the United States in order to identify the effect of spatial variation of the climate change hazard.

2. Climate change

Natural and anthropogenic factors have forced an overall change in the climate. Sea level rise, increasingly intense precipitation, and increasingly intense hurricanes are among the major components of climate change that affect riverine bridges [1,21]. Heat waves, arctic warming, and increased temperature and humidity may also affect the life-cycle performance of civil infrastructure [1,22,23]. Together, all of these aspects define the climate change hazard and may have adverse effects on the performance of civil infrastructure [5,22]. This paper will focus on the changes in flooding that accompany the climate change hazard. Alternative aspects of the climate change hazard may also be included, but since hydraulic events (including scour, debris impact, debris accumulation, among others) are the predominant source of damage to bridges [24], river discharge and flooding are the main hazards considered herein. It is important to note, however, that the framework and concepts presented in this paper for the development of optimal adaptation strategies for riverine bridges can be applied to other aspects of climate change for other civil infrastructure systems.

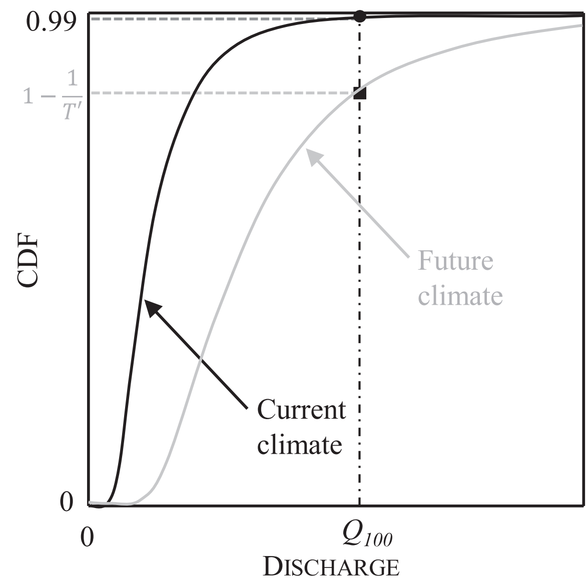

Fig. 1. The cumulative distribution of discharge for a current and future climate.

The change in flooding is typically described by a change in the return period of a discharge of a specific magnitude; typically, this is the discharge associated with the 100-year flood [25–27]. The 100-year flood discharge under the current climate, denoted herein as Q_{100}, is associated with a probability of exceedance of 0.01, as shown in Fig. 1. A statistical analysis of outputs from GCMs at the end of a period of time provides the probability of exceedance of the Q_{100} discharge for a future climate. The climate change is then reported as a change in the recurrence interval of the 100-year flood; in Fig. 1 the future recurrence period is denoted as T'.

The predicted climate change effect on flooding varies for different RCPs and different GCMs. Thus, a set of future recurrence intervals exists for a specific location rather than a single value. Since no likelihoods can be assigned to the different RCPs [5] and no agreement (at this time) can be made on which GCM is most accurate [16], no likelihood can be assigned to the set of future recurrence intervals; the scenario uncertainty and model uncertainty are both sources of deep uncertainty.

Hirabayashi et al. [27] provided insight into the changes into the spatial variation of global flooding. The outputs from 11 GCMs for RCP 8.5 were used to obtain a change in the return period of the 100-year flood for various rivers across the world. The minimum, 25th percentile, median, 75th percentile, and maximum return periods from the 11 outputs were reported for rivers across all continents. Two rivers in the United States were reported: the Mississippi and the Columbia. The expected climate trends in these rivers are detailed in Fig. 2.

The predicted shifts in the return periods for these two rivers highlight two main points: (1) the variation in GCMs is significant and may be contradictory. For the Columbia River, 8 out of 11 models determined that the return period would decrease, leaving 3 models suggesting that the return period would increase [27]. This can also be interpreted as 8 models indicate an increase in Q_{100}, while 3 indicate a decrease. For the Mississippi River, 7 out of 11 models determined that the return period would increase, leaving 4 models suggesting that the return period would decrease. (2) It is essential to consider the spatial